Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4, 262-275
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i4.5983
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An intelligent system for college admission queries: Leveraging BERT and Siamese BiLSTM for enhanced accuracy

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Abstract: College admission is a critical process that is pivotal in shaping a student's academic and professional future. College admissions queries include an extensive range of issues, from application standards and qualifying criteria to financial assistance and campus life. This research presents an intelligent system designed to address college admission queries with enhanced accuracy and efficiency. The system leverages the power of Bidirectional Encoder Representations from Transformers (BERT) and Siamese Bidirectional Long Short-Term Memory (Siamese BiLSTM) architecture to process and understand complex, context-dependent inquiries posed by prospective students. The data is sourced from multiple channels, such as historical admission records from the university's website and interaction logs from previous counseling sessions. The data was preprocessed using tokenization and lemmatization to avoid redundancy. Term Frequency-Inverse Document Frequency (TF-IDF) employed for feature extraction quantifies the query terms, allowing the system to identify significant words and improve query classification. a Siamese BiLSTM model was proposed for improved question classification and similarity matching. BERT generates contextual word embeddings that capture the semantic meaning of the words in the user's query. The system is capable of accurately classifying and understanding user queries, ensuring that responses are both contextually relevant and precise. Findings show that the proposed system achieves accuracy (94.7%), precision (93.6%), recall (93.8%), and F1-score (92.3%) while leveraging Python (version 3.x) for implementation. The results show that this integrated system outperforms traditional keyword-based query response systems, offering a more robust, scalable, and accurate solution for college admission-related queries.

Keywords: *Bidirectional encoder representations from transformers (BERT), College admission queries, Siamese bidirectional long short-term memory (Siamese BiLSTM), Students.*

1. Introduction

The intelligent systems in educational settings have changed the way institutions respond to inquiries from potential students. College admissions, a very important process for both students and institutions, typically involves answering numerous questions on everything from application deadlines and eligibility criteria to financial aid options and course details [1]. These queries must be addressed promptly and accurately to promote positive engagement and help students make informed decisions [2]. The promise in deep learning models like BERT and Siamese BiLSTMs have made headways into the complexities of natural language inputs and shown remarkable promises towards understanding, while BERT utilizes the powers of contextual word embeddings, together with semantic similarity analysis to solve with proper and relevant contexts [3]. The novelty of that approach is its ability to combine the strengths of contextual embeddings and similarity analysis for improved accuracy. When the conventional methods system is designed for handling diverse linguistic styles, efficiently with large

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History: Received: 20 January 2025; Revised: 26 March 2025; Accepted: 31 March 2025; Published: 4 April 2025
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datasets, and providing accurate answers to users' queries [4]. user experience is improved and saved the workload from human administrators that institutions can apply to other very critical aspects of the admission processes [5]. There are many challenges in applying intelligent systems for college admission queries. Traditional query resolution systems are normally rule-based or rely on pre-built templates, fail to understand multiple linguistic variations, and cannot make sense of many complex sentence structures [6]. With questions from students having different linguistic and cultural backgrounds that are presented in different styles, these systems quite often fail to provide the answer sought. Not being able to identify semantically similar questions has also proved an obstacle for the system. Scalability is another matter of urgency [7]. As the application numbers are going up, universities need systems that can process big volumes of questions without sacrificing the quality of responses. Where conventional systems fail, delays, inaccuracy, and dissatisfied users are common casualties [8]. Historically, the domain of query resolution was dominated by rule-based systems. Such systems operate according to a predefined set of rules and keywords, using them to match queries with appropriate responses [9]. These are very simple and straightforward to implement, but they lack adaptability to changes in linguistic patterns and cannot process complex, context-sensitive queries [10]. To address these limitations, the usage of advanced deep learning techniques BERT and Siamese BiLSTMs would be applied in formulating an intelligent system that could effectively respond to college admission queries. BERT itself is a pre-trained transformer-based model that works on contextual nuances within text, hence the system will be capable of understanding complex queries. With Siamese BiLSTM as the specialization in terms of recognizing semantic similarity, the approach will ensure the suitability and matching of user's queries with relevant responses even with their significantly different phrasing. This work aims to develop an intelligent system that uses BERT and Siamese BiLSTM to accurately classify and respond to college admission queries, thus improving response precision, scalability, and user experience for prospective students and educational institutions. The main contributions of this work are:

- BERT was used to generate contextual word embeddings and Siamese BiLSTM for improving question classification with accuracy and similarity matching toward perfect understanding and resolution of complex queries over college admission.
- The proposed system highly improves the accuracy and relevance of query responses as compared to existing keyword-based approaches, providing greater satisfaction in decision-making for prospective students.
- The system provides a rich and extensible framework to handle large volumes of diverse admission-related queries, thus streamlining communication between institutions and prospective students.

The research is as follows: Phase 2 covers the literature review, Phase 3 focuses on the proposed system design, Phase 4 presents the performance evaluation and discussion, and Phase 5 includes the conclusion, limitations, and future scope.

2. Literature Review

A new method for Knowledge Graph Question Answering (KGQA) suggested by Chong, et al. [11] was that sentence Transformers use TransKGQA to improve contextual comprehension and flexibility across a range of knowledge areas. With an F1 score of 78%, question-answer pair augmenting and a threshold system was used to ensure dependable answer retrieval, aiding in the creation of knowledge graphs and automated running of Cypher queries. The Knowledge-Infused Medical Abstractive Generator (KI-MAG) was an innovative knowledge-infused abstractive query answering system designed especially for the medical industry approach [12]. accuracy and dependability in safety-critical medical settings was enhanced and abstractive QA's drawbacks, including large training data sets and inaccurate entities were tackled. The objective of Community Question-Answering (CQA) forums was to respond to users' inquiries in a timely and appropriate manner [13]. Bridging the lexical gap between inquiries could be challenging. the translation-based language method that employs transformer-based

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methods and metadata was enhanced. The suggested strategy outperformed all state-of-the-art techniques in question retrieval, achieving 51.47 in terms of mean average precision (MAP).

To address multi-hop query-resolving issues, an experimental design known as the Dependent Syntactic-Semantic Augmented Graph Network (DSSAGN) was developed [14]. In contrast to earlier models, scalability, interpretability, and accuracy were provided by utilizing syntactic patterns and semantic linkages found in knowledge networks. Multimodal question answering (MMQA) was a difficult problem that combines computer vision and the processing of natural languages has been suggested [15]. Although text-based methods had shown promise, the outcomes had been disappointing. cutting-edge methods was used for answer creation, context retrieving, and unified knowledge representation. The Stanford question answering database benchmark data and distilBERT were used by Farea and Emmert-Streib [16] to assess extractive question-answering (EQA) algorithms. The way answer length affects performance, how exact match metrics vary, and how useful various definitions were in real-world situations have been examined. The findings raise questions regarding the reliability of reported results because the findings demonstrate that variations among several exact match measurements were comparable to those reported in the literature. The use of large vision-language models (LVLMs) and large language models (LLMs) in remote sensing image processing was examined by Bazi, et al. [17] with a focus on query resolving and image captioning. The efficacy of the large language and vision assistant technology in remote sensing (RS) image analysis was demonstrated by introducing an enhanced version of the model. The Fine-Grained Question Subjectivity Dataset (FQSD) addressed the gaps examined in Babaali, et al. [18] in automatic subjective question answering (ASQA) technologies, providing a comprehensive dataset for question subjectivity classification. The 10,000-question dataset provided further classifications and separated subjective and objective questions. It was remarkable that a 97% F1-score validated the dataset's effectiveness for the complex subjectivity categorization task. The Medical Visual Question Answering (VQA) assignment required reasoning using both visual and written information approaches [19]. A new method using Cross-Modal pre-training with Multiple Objectives (CMMO) was introduced, leveraging datasets of public medical images with captions. Experimental results show improvements of 2.6%, 0.9%, and 4.0% on three public medical VQA datasets. In education, question generation (QG) was becoming more popular as a way to create questions that were appropriate in complexity for each learner's reading level [20]. Considering item response theory and an adaptive QG structure that suggested a technique for creating question-answer pairings according to difficulty. Tests demonstrated that the suggested approach could produce question-answer pairings that were appropriate for students' skill levels. To use a randomized visual question answering (VQA) dataset was used to assess the resilience of a cutting-edge VQA model [21]. Results indicate that the model had trouble predicting "unknown" answers or giving erroneous results. To tackle that issue, Cross-Modal Augmentation (CMA) was suggested, a multi-modal semantic augmentation method that was independent of the model and only applies during testing. Pathology (PathVQA) was a prospective medical tool that relies on language and vision interactions to respond to approaches [22]. Current approaches had difficulty interpreting retrieved replies and capturing high- and low-level interactions. A vision-language transformer was presented to overcome these constraints. Several variables, including design, data, parameters, and tasks, affect how well natural language processing models perform suggested [23]. By offering a model for multitasking that generated a range of reference materials as evidence for yes/no questions. The approach performed better than conventional training techniques, giving users insightful information and improving the user experience. The possibility that general-purpose Pre-trained language models (PLMs) could outperform domain-particular PLMs without requiring expensive retraining was investigated [24]. The authors suggested a self-supervised technique for training a classification algorithm that systematically chooses the PLM most likely to provide the right answer to the query using the Biomedical query answering task. With a 14.2% improvement with larger models and a 16.7% improvement with lighter ones on average. Natural language processing's Open-domain question answering (OpenQA) challenge was challenging to examine [25]. Conventional approaches entail

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locating pertinent documents and extracting responses. OpenQA had demonstrated the effectiveness of deep learning approaches, but Arabic had not gotten as much attention. In two Arabic benchmark datasets, the model enhanced the end-to-end question-answering system and performed better than the conventional technique in terms of passage retrieval accuracy.

3. Proposed System

The College Admissions dataset was used to contain academic records, test scores, and admission statuses to solve complex college admissions queries. Preprocessing would include tokenization or splitting the text into smaller units of text, then lemmatization, which reduces words to their base forms, so that there is consistency and absence of redundancy. Features are extracted using TF-IDF to describe the significant terms and BERT to generate contextual embeddings. a Siamese BiLSTM method, which discovers semantic relationships, and contextual dependence within the questions for proper classifications and context-ambiguity-resolution regarding questions of admission-related matters, was utilized. The flow of efficiency resolving college admission queries is depicted in Figure 1.

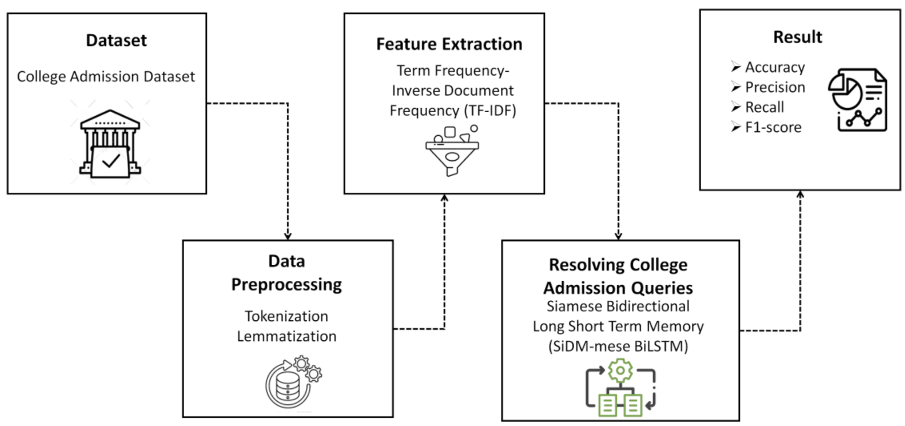

Figure 1.
Overflow of efficiency resolving college admission queries.
Source: https://www.kaggle.com/datasets/samsonqian/college-admissions.

3.1. Dataset

The College Admissions dataset on Kaggle explains a lot about college admission decisions in detail, including records of students' academics, test scores, and admission status. Such a dataset can be incredibly helpful in training models to predict admission outcomes, but it would likely demand additional processing and enrichment specifically for query resolution tasks related to college admissions.

3.2. Preprocessing Using Tokenization and Lemmatization

Data is preprocessed through the techniques of tokenization and lemmatization to eliminate redundancy and promote a consistent understanding of queries based on college admission. Tokenization splits text into smaller units named tokens, whereas lemmatization converts words to their roots or base words to improve query classification and similarity matches for the easy processing and effective comprehension of such complex admission-based queries.

3.2.1. Tokenization

Tokenization is to develop an efficient strong college admission query system that improves query resolution accuracy and efficiency through advanced preprocessing and text analytical techniques. The first stage converts HTML files to text by removing HTML tags and other elements. Any kind of preprocessing of conversational text is generally referred to as tokenization. The practice of replacing

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sensitive data with unique identifying symbols while preserving all pertinent information about the material without sacrificing security is known as tokenization. In addition to splitting lines into basic units of processing, enhanced tokenization is the act of analyzing and combining isolated tokens to create more sophisticated tokens. For the college admission query system, preprocessing and textual unit segmentation are applied to raw texts. Three steps must be taken to process the data: first, the document must be converted to word counts, which correspond to a bag of words (BOW). The second action is eliminating empty sequences, which includes filtering and cleaning (e.g., deleting unnecessary control characters, and whitespace compressing). Lastly, a list of features, also known as tokens, words, phrases, or attributes, is extracted from each input text document.

3.2.2. Lemmatization

Lemmatization is to develop and improve the response accuracy in relevance for college admission query processing by introducing advanced natural language techniques like lemmatization and contextual embedding. Lemmatization is a text preparation method that gives words their base or canonical form, or lemma, by removing their inflectional endings. Lemmatization guarantees that the produced lemma is a legitimate word in the language, similar to the outcome provided by stemming. Through lemmatization, words to do with the application process, such as "applying" or "applications," will be lemmatized into their root forms, which may be either "apply" or "application." The accuracy in solving queries is maximized. In contrast to stemming, which could produce a non-word such as "intelligent," lemmatization ensures that the lemma that is produced is a legitimate and identifiable word. By producing linguistically relevant lemmas, lemmatization improves text analysis and facilitates finding data, language comprehension, and other processing critical for the accuracy and relevance of responses in college admissions query processing using BERT.

3.2.3. Term Frequency-Inverse Document Frequency (TF-IDF) Using Feature Extraction

TF-IDF quantifies the terms in the query of college admissions to extract the significant features. It helps the intelligent system to focus on finding the critical terms associated with queries of college admissions so that proper query classification and resolution are ensured. It allows a system to identify the significant words and pay proper attention to relevant content in the classification and resolution of a query. The first step in this feature extraction process is to calculate the $TF-IDF$ score for a given document. This score facilitates consideration of the most important features in the dataset so that the system could have better ideas of the context-dependent queries asked by the potential students. The dataset is subjected to the $TF-IDF$ formula represented in Equation (1).

$$TF-IDF = TF * IDF \tag{1}$$

TF is defined as the ratio of a feature's frequency of occurrence in a document to the overall amount of features in the text document. IDF Simultaneously assesses a feature's capacity for category differentiation. Keep in consideration that the categories listed below correspond to the text document's defined class label. By using$TF-IDF$, the proposed system will be able to distinguish terms essential for different query contexts in college admissions. the formula for expressing TF and IDF are represented in Equations (2) and (3).

$$TF = \frac{FFTD}{TFTD} \tag{2}$$

$$IDF = log\frac{NDF}{TD} \tag{3}$$

Where $TFTD$ is the overall amount of times a word appears in a text document, and $FFTD$ is the frequency of a feature appearing in a text document. For theIDF, TD is the overall amount of documents, and NDF is the amount of documents that include the feature. Higher $TF-IDF$ scores indicate terms that are crucial for proper classification and better system responses to complex admission-related queries. A feature's significance for a given text document increases with its $TF-IDF$ score.

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3.2.4. Enhanced Query Classification and Matching for College Admissions Using Siamese BiLSTM

The Siamese BiLSTM method is implemented because it can properly capture semantic similarity and contextual relations in queries; this allows accurate question classification as well as matching, which supports the accuracy in resolving college admissions queries. To develop an intelligent system by utilizing the Siamese BiLSTM capacity to handle complex, context-dependent queries efficiently in the resolution of college admissions inquiries. The three modules that comprise the Siamese BiLSTM model are $Na, Nb, and\ Nc$. Different inputs are given to the various module configurations. Only the dissertation is sent to the module that comprises$Na\ and\ Nc$; distance information is sent to $Nb\ and\ Nc$; and the essay and samples are sent to $Na, Nb, and\ Nc$. The three pairings provide distinct outcomes. The most terrible is the first, the medium is the second, and the most desirable is the third. This supports earlier theory that better scoring outcomes are obtained with more scoring information input. The specifics will be covered in the section. The Siamese BiLSTM architecture is illustrated in Figure 2.

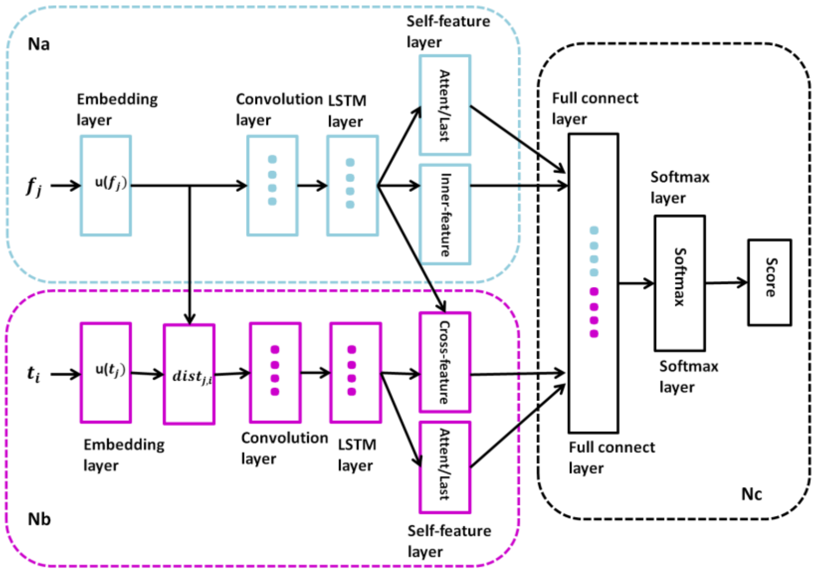

Figure 2.
Siamese BiLSTM Architecture.

3.2.5. Embedding Layer

The embedding layers to improve representation as well as the understanding of features in systems that classify college admission queries. An essay t_i and a sample f_j are included in every pair that the algorithm accepts as a training instance. The paragraph appears as a fixed-length sequence, with each series being extended to the greatest length, as seen in Figure 2. Each order is subsequently changed into a set of less dimensional variables by the layer of embedding. It uses the operator u to express the word embedding technique. The word embedding results are$u(f_j) \in \mathbb{R}^{|U|\times C}\ and\ u(t_j) \in \mathbb{R}^{|U|\times C}$, where C is the word embedding dimensionality and $|U|$ is the vocabulary's length.

Following word embedding, the distance knowledge between essays$u(f_j) and\ u(t_i)$ is represented by$dist_{j,i} = u(f_j) - u(t_i)$. This helps in better feature representation, especially for lower data volumes, as the model is trained with improved distance-based knowledge. This layer is applied because word embeddings effectively reduce the dimensionality with the preservation of contextual relationships that are critical to downstream classification tasks.

3.2.6. Convolution Layer

ISSN: 2576-8484
Vol. 9, No. 4: 262-275, 2025
DOI: 10.55214/25768484.v9i4.5983
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The convolution is to improve local pattern recognition accuracy with increased accuracy of feature extraction in college admission query systems. Especially for short articles, choosing and omitting this layer, which is an optional decision that contains the fewest examples and the greatest average length, performs the convolutional process. It provides a detailed overview of the dataset. The dense description of the long incoming data sequence is generated and delivered to the network's LSTM layer. This convolutional layer helps to capture local patterns in short essays, thus providing further improvement in the accuracy of feature extraction. Applying a convolution layer to the embedding layer's output will enable this optional feature.

3.2.7. LSTM Layer

To improve the sequential understanding with an enhancement of features to achieve an accurate college admission query classification through the LSTM network. An LSTM network receives the string of word embeddings that have been obtained from the embedding layer (also known as the convolution layer) as represented in Equation (4).

$$g_s = LSTM(g_{s-1}, w_s) \quad (4)$$

Where the input parameters at time s are denoted byw_s and g_s. The information flow inside the recursive procedure is controlled by the input, output, and forget gates that construct the LSTM model. The LSTM function is officially described by the following Equation (5) to Equation (10).

$$j_s = \sigma\left(X_j . w_s + V_j . g_{s-1} + a_j\right) \quad (5)$$

$$e_s = \sigma(X_e . w_s + V_e . g_{s-1} + a_e) \quad (6)$$

$$\widetilde{D}_s = tanh(X_d . w_s + V_d . g_{s-1} + a_d) \quad (7)$$

$$\widetilde{D}_s = j_s \circ \widetilde{D}_s + e_s \circ \widetilde{D}_{s-1} \quad (8)$$

$$p_s = \sigma\left(X_p . w_s + V_p . g_{s-1} + a_p\right) \quad (9)$$

$$g_s = p_s \circ \tanh\,(d_s) \quad (10)$$

The hidden vector g_s, which represents the essay's semantic structure at location s, is the output by LSTM at each time step s. In the Self-information layer, the essay's final description is once more feature-extracted. This layer guarantees the learning of essay features in an exact sequential manner by Bidirectional LSTM, using both forward and backward dependencies.

3.2.8. Self-Feature Layer

To enhance the contextual and relational feature extraction for the accurate classification of queries using the self-feature layer. This layer describes how to use the vector data acquired from the bidirectional LSTM layer to get the self-feature. It makes an effort to describe these relationships since it is thought that the distance information vector value is$dist_{j,i}$and the essay's data vector value is $f_j$ought to possess some exterior relations and the adjacent sentences might have certain inner connections.Let gf be the hidden layer representing the essay, and gf_s represent the value of the vector at location$s$ of gf; when gcbe the value of the hidden layer for the distance knowledge, and gf_s represent the vector at location s of gc. Assuming that sentence lengths are constant across sentences, let δ be the sentence length. To calculate the vector gf similarity at positions s and $s + \delta$, which refers to it as an inner feature is represented in Equation (11).

$$inner - feature = \frac{gf_s \cdot gf_{s+\delta}}{|gf_s| \cdot |gf_{s+\delta}|} \quad (11)$$

To calculate the similarity between vectors gf and gc at the same point s; this similarity is known as a cross-feature represented in Equation (12).

$$cross - feature = \frac{gf_s \cdot gf_s}{|gf_s| \cdot |gf_s|} \quad (12)$$

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Equations (11) and (12) use · as a dot product. The inside and cross features are then delivered to the next layer after being combined into vectors that have been referred to as internal and cross characteristics directly. The composition's secret layer and the distance-based data secret layer are its two main outputs, in addition to inner-feature and cross-features. The model reaches improved internal and cross-feature extraction, resulting in a better representation of relational and contextual features indispensable for classification tasks. These two layers have two processing options. There are two methods: taking the mean vector throughout time or taking the vectors at the final positions of $gf \text{ and } gc$ directly. These two vectors are referred to as $gf - vector \text{ and } gc - vector$.

3.2.9. Fully-Connected Layer

The fully connected layer is to integrate and combine the features extracted for the comprehensive classification of queries with enhanced accuracy. Four vectors the $gf - vector, gc - vector$, inner-feature, and cross-feature is then acquired from the information about self layer. These four vectors can be concatenated into a single one. The concatenated vector is then sent to the Softmax layer.This layer combines all features extracted, providing holistic learning over the interaction between queries and training information.

3.2.10. Softmax Layer

To classify the output efficiently to ensure accurate categorization of the query for improved resolution of admission queries. The purpose of this layer is to categorize the fully linked layer's output. By using Equation (13), it is classified.

$$t(w) = sigmoid(x.w + a) \tag{13}$$

In the above equation x is the value of the weight vector, a is the value of the bias, and w represents the source vector. This layer is applied because it helps in the efficient classification of outputs as it maps the probabilities to the predefined categories quite effectively.

3.2.11. Performance Evaluation

The experimental setup used a system with at least 16 GB RAM and a very powerful GPU NVIDIA Tesla, taking advantage of deep learning functionality. The software stack includes Python, and TensorFlow, along with libraries that include BERT for NLP and Siamese BiLSTM to classify and match queries are in Table 1.

Table 1.
Experimental Setup.

Component	Specification
RAM	16 GB or higher
GPU	NVIDIA Tesla
Software	Python, TensorFlow
Libraries	BERT, Siamese BiLSTM, NLP libraries
Operating System	Ubuntu or Windows 10/11

The tokenization uses the college admission dataset, which is fundamental in the context of tokenization in pre-processing. This involves breaking up the complex text, for instance, names of universities, into much smaller, easier-to-process units. These are known as tokens, each being a word or meaningful symbol that machines like BERT and Siamese BiLSTM understand. A query such as "What are the eligibility requirements for admission?" and "Is there a deadline for submitting applications?" makes the analysis more efficient by focusing on the core meaning of each word. This pre-processing ensures that the input data is prepared for deeper analysis so that the model can answer college admission queries with greater accuracy through token-level patterns. Tokenization helps break

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down complex phrases into structured data for better model performance. The tokenization result is illustrated in Table 2.

Table 2.
Tokenization Outcome for College Admission Query Analysis.

Original Text	*Lemmatized Tokens*
"Apply for admission"	*["Apply", "for", "admission"]*
"What are the eligibility requirements for admission?"	*["What", "are", "the", "eligibility", "requirement", "for", "admission"]*
"Is there a deadline for submitting applications?"	*["Is", "there", "a", "deadline", "for", "submit", "application"]*
"What is the application fee?"	*["What", "is", "the", "application", "fee"]*
"Can I apply for financial aid?"	*["Can", "I", "apply", "for", "financial", "aid"]*

A lemmatized dataset is used for college admission, which is essential for preprocessing in lemmatization reducing words to their base or root form, ensuring uniformity and facilitating better analysis by machine learning models on text. The data consists of university names accompanied by a set of associated numerical attributes such as enrollment numbers and admission-related metrics. The entry " 6142 5521 104 15 88 370 450 350 450" would reduce to the following lemmatized tokens such ["6142", "5521", "1104", "15", "88", "370", "450", "350", "450"]. This pre-processing phase would thereby make the model pay attention to suitable patterns only, thereby enhancing its ability to handle diverse admission queries. It simplifies and standardizes the data, allowing the application of BERT and Siamese BiLSTM models, thus enhancing their ability to process and interpret admission-related queries with precision. The lemmatized result is illustrated in Table 3.

Table 3.
Lemmatization Outcome for College Admission Query Analysis.

Original Text	*Lemmatized Tokens*
"6142 5521 1104 15 88 370 450 350 450"	["6142, 5521, 1104, 15, 88, 370, 450, "350", "450"]
" 5689 4934 1773 693 520 640 520 650"	["5689, 4934, 1773, 6, "93", "520", "640", "520", "650"]
" 626 326300 313 202 111 6 3 3"	["300", "313", "202", "111", "6", "3", "3"]
" 2054 1656 651 34 94 510 640 510 650"	[2054, 1656, 651, 34, 94, 510, 640, "510", "650"]
" 10245 5251 1479 18 87 380 480 370 480"	["10245", "5251", "1479", "18", "87", "380", "480", "370", "480"]

An optimized query resolution system utilizes advanced deep learning techniques such as BERT and Siamese BiLSTM to attain performance metrics of an optimized query resolution system at different training epochs (20, 40, 60, 80, and 100). At 20 epochs, the system averages 1.2 seconds in query resolution time, processes 350 queries per hour, and scales at 0.25 queries per second. With epochs increased to 40, the resolution of queries improves to 1.1 seconds, processing 375 queries per hour with scalability at 0.27 queries per second. With the increase of epochs to 60, the resolution time drops to 1.0 seconds, processing 400 queries per hour with a scalability of 0.30 queries per second. The system resolves queries at 80 epochs in 0.9 seconds, with 425 queries per hour, and scales up to 0.32 queries per second. Then, finally, at 100 epochs, it achieves the best performance with 0.8 seconds, 450 queries per hour, and 0.35 queries per second scaling, where major efficiency improvement has been witnessed. These values are illustrated in Table 4 and Figure 3.

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Table 4.
Performance Metrics with Time of the Optimized Query Resolution System.

Epochs	Query Resolution Time (Avg. seconds)	Number of Queries Processed per Hour	Scalability (Queries per Second)
20	1.2	350	0.25
40	1.1	375	0.27
60	1.0	400	0.30
80	0.9	425	0.32
100	0.8	450	0.35

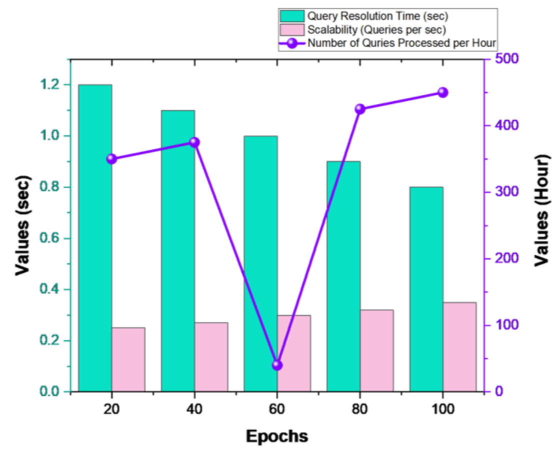

Figure 3.
Performance Analysis Result with Time of the Query Resolution System.

The exceptional performance of the optimized query resolution system with a response accuracy of 91.4% showed it was capable of answering queries accurately. Its efficiency in understanding the query was at 90.2%, reflecting its ability to interpret context and intent. It also had an impressive robustness rate of 98.3% in handling a variety of queries. The system underscores its effectiveness in delivering a seamless, reliable query resolution of college admissions, with a user experience satisfaction rate of 92.1%. These values are illustrated in Figure 4 and Table 5.

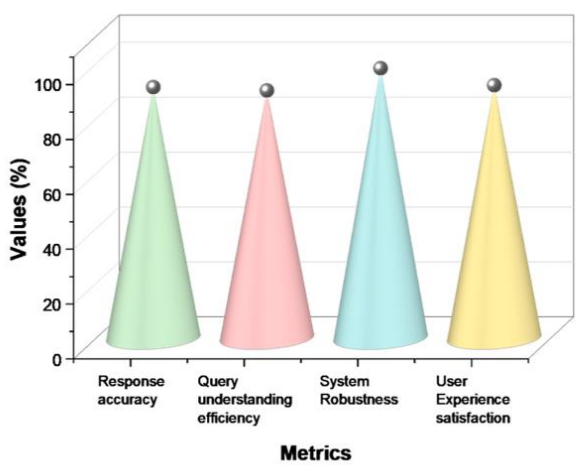

Figure 4.
Performance Analysis Result in Percentage of the Query Resolution System.

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Table 5.
Performance Metrics in Percentage of the Optimized Query Resolution System.

Metric	Optimized Query Resolution System
Query Resolution Time (Avg. seconds)	1.2 sec
Number of Queries Processed per Hour	350
Scalability (Queries per Second)	0.25 sec
Response Accuracy (%)	91.4 %
Query Understanding Efficiency (%)	90.2 %
System Robustness (Successful Query Handling)	98.3%
User Experience Satisfaction (%)	92.1%

The Multinomial Naive-Bayes [26] method is the existing method compared to the proposed Siamese BiLSTM method in resolving college admission queries. The characteristics of accuracy, precision, recall and f1-score are examined in this section.

Accuracy and Precision: The Multinomial Naive-Bayes method reached accuracy (92%), and precision (92.4%). The Siamese BiLSTM method outperformed with accuracy (94.7%), and precision (93.6%). These results show that the Siamese BiLSTM, by using contextual embeddings through BERT, provides improved query classification and similarity matching and offers a more robust and accurate solution for automated college admission query resolution. The accuracy and precision value of college admission query resolution is illustrated in Figure 5 and Table 6.

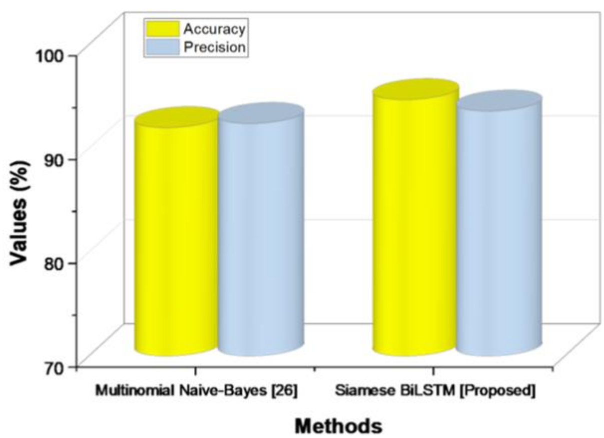

Figure 5.
Accuracy and Precision Result of College Admission Query Resolution.

Recall and F1-Score: The Multinomial Naive-Bayes results yielded a recall (92%) and an F1-score (91.9%). The Siamese BiLSTM produced recall (93.8%) and F1-score (92.3%), as shown by a much stronger capacity of this Siamese BiLSTM to learn more abstract and deeper semantic relations than those between simpler contexts within queries. It presents some efficiency on further accuracy as well as on intricate query resolutions about this work leveraging BERT Embeddings alongside its Siamese BiLSTM architecture. The recall and f1-score value of college admission query resolution are illustrated in Figure 6 and Table 6.

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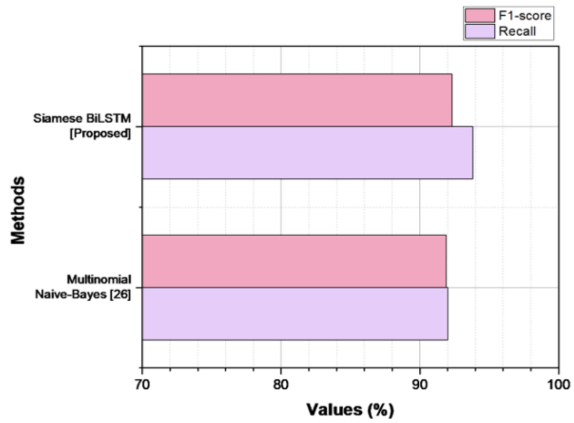

Figure 6.
Recall and F1-Scoreresult of College Admission Query Resolution.

Table 6.
Performance Comparison Outcome of College Admission Query Resolution.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Multinomial Naive-Bayes [26]	92%	92.4%	92%	91.9%
Siamese BiLSTM [Proposed]	94.7%	93.6%	93.8%	92.3%

4. Discussion

An optimized query resolution system was developed, leveraging deep learning techniques such as Siamese BiLSTM to capture semantic similarity and contextual relationships for proper classification and resolution of complex queries on college admissions. Multinomial Naive-Bayes [26] with accuracy (92%), precision (92.4%), recall (92%), and F1-score (91.9%), suffers from limited context and semantics capturing capability of the query that leads to potential loss in accuracy for more nuanced or complex questions.

The proposed Siamese BiLSTM method overcomes the limitations of Naive-Bayes by using deep learning to understand semantic relationships and context. While Naive-Bayes works based on the frequency of words and simple probabilities, Siamese BiLSTM captures contextual meaning through word embeddings. This method significantly improves the accuracy of classification as it can tackle more complex queries and ensure that the responses are relevant and precise. It uses the BERT architecture for contextual word embedding to further enhance the ability of the system to handle context-dependent queries.

5. Conclusion

An intelligent system that uses BERT and Siamese BiLSTM to answer college admission questions with high accuracy. BERT produces contextual embeddings, and Siamese BiLSTM captures semantic similarity and contextual relationships, which allows for accurate query classification and resolution. The system processes complex queries through tokenization, lemmatization, and TF-IDF-based feature extraction. It greatly outperforms traditional keyword-based methods, with a robust, scalable, and efficient solution that enhances user experience for future students and supports educational institutions with high volumes of admissions-related inquiries. The proposed system achieves notable results, including accuracy (94.7%), precision (93.6%), recall (93.8%), and an F1-score (92.3%), underscoring its effectiveness in resolving college admission queries compared to conventional methods.

5.1. Limitation and Future Scope

The limitation arises from its reliance on high-quality labeled data and computational resources while the Siamese BiLSTM is highly capable of good generalization capability across different queries

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and institutions. This future scope might include increasing its dataset with richer queries, along with multilingual support, incorporating advanced transformers to maximize accuracy, as well as calibrating it to various academic platforms around the globe.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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